

UTILIZING AN EQUITY INDEX MODEL TO ASSESS TREE-PLANTING NEED IN FREDERICK COUNTY MARYLAND

A.B. Tilson¹, M. Heckert*¹, E. Goodnough²

¹Department of Geography and Planning

West Chester University of Pennsylvania

Fifth Floor, Business and Public Management Center

50 Sharpless Street

West Chester, PA 19383

²Maryland Department of Planning

301 W. Preston Street, Suite 1101

Baltimore, MD 21201

ABSTRACT: *As communities adopt mitigation efforts to alleviate the effects of climate change, it is imperative to consider how these initiatives impact the most vulnerable populations. This paper takes a needs-based definition of equity and a Geographic Information Systems (GIS) approach to modelling several scenarios for the study area of Frederick County, Maryland. The outcomes illustrate how areas of greatest need are spatially distributed and fluctuate based on the inclusion or exclusion of variable inputs related to the built environment, demographics, and the concept of feasibility. A key finding is how excluding a variable like high-density residential land use can ignore lesser resourced areas for policy decisions targeting relatively better off regions. Need, to varying degrees and definitions, exists throughout Frederick County, making an equity index model a valuable tool for policy makers and community members to increase participatory planning from those who are directly affected by policy methods, decision making, and implementation.*

Keywords: *Equity, climate change, equity index model, GIS*

INTRODUCTION

The overwhelming consensus of scientific research validates that climate change is real and human-caused (Lynas, Houlton, and Perry 2021). As global warming continues at current rates, the effects will be significant, with outcomes including increasing average and extreme temperatures (Hacker and Roberts 2013), increased natural disaster frequency and intensity (Horney et al. 2021), sea level rise and ocean acidification (Dvorak et al. 2018; Doney et al. 2020), and the subsequent devastating societal implications (Rossati 2017). Afforestation initiatives to offset the effects of climate change have gained tremendous support in recent years. Global campaigns like Trillion Trees, WeForest, and Ecosia aim to plant an immense number of trees spanning a diverse set of climates and regions to sequester carbon from greenhouse gas emissions (Seddon et al. 2021). In addition to trapping carbon, trees offer many beneficial aspects for surrounding natural and human communities. Tree planting is economically viable (Nijnik et al. 2013; Plantinga, Mauldin, and Miller 2017; Hou et al. 2019; Mader 2019). Trees provide numerous physical and mental health benefits (Beyer et al. 2014; Ulmer et al. 2016). Trees can increase property values (Dimke, Sydnor, and Gardner 2013). Trees reduce air and light pollution (Nowak et al. 2014; Straka et al. 2021), reduce urban heat island effect (Knight et al. 2021), manage stormwater runoff (Kuehler, Hathaway, and Tirpak 2017), and provide vital habitats to declining or endangered animal populations (Mackay, Gross, and Rossetto 2018). As governments and nonprofit organizations continue to include afforestation initiatives in their toolkit of programs fighting climate change, greater emphasis must be placed on where trees are planted, who is experiencing the benefits, and how these decisions impact local communities. Efforts to curtail an already inequitable situation are paramount. This paper will use Frederick County, Maryland as a case study to evaluate the use of an equity index in decision making related to afforestation. The index will evaluate variables of equity and the concept of feasibility for afforestation, while discussing three scenarios of different index outcomes.

Equity

To assess the outcomes of existing tree locations and prospective projects, equity should be defined. For the purposes of this paper, equity will refer to a needs-based approach to assessing fairness. This definition differs from alternative ways of viewing equity (e.g., desire, quality, capability), and is an important distinction when evaluating the physical, emotional, and built environment in which trees contribute greatly. Unfortunately, the negative effects

of climate change will be experienced at greater rates for vulnerable and underserved communities, and the numerous benefits from trees are often not experienced by all groups. Studies have found links between inequitable distribution of trees, and subsequently greenspace, and race (Watkins and Gerrish 2018; Lin and Wang 2021), children (Rigolon and Flohr 2014; Łaskiewicz and Sikorska 2020), elderly (Zandieh, Martinez, and Flacke 2019), low-income areas (Rigolon 2016), and urban environments (Lin, Meyers, and Barnett 2015). As such, identifying areas with the highest need for immediate afforestation relief will be considered through the lens of several demographic and built-environment variables.

The intention of this model is to provide a multitude of variables related to historically disadvantaged regions highlighted by the demographic and built environment. In doing so, the model presents several options for the user to include or ignore in their assessment of the study area. The potential bias from the type of organization engaged in the greening initiative can be limited. Research has shown how funding sources, community relationships, and general resources can skew afforestation efforts of nonprofit and municipal organizations. An analysis of afforestation outcomes across nonprofit and municipal programs found an interaction between variables of race, tree canopy cover, and income (Watkins et al. 2017). Communities with higher percentages of African Americans experienced less likely instances of afforestation programs. Also, among communities with the greatest need for trees, exhibiting lowered income levels and rates of existing tree canopy cover, larger African American populations were selected as sites for afforestation programs at even lower frequencies. Removing the influence of the organization's missions and resources from the initial identification of where to launch a greening program can help reduce these biases or lessen the extent to which an already inequitable distribution is exacerbated.

Additionally, the index model is created in such a way that allows for applications related to alternative methods of defining equity. Haase et al. (2017) compiled six prerequisites aimed at achieving social inclusion as it relates to greening projects framed in the sustainable and equitable development space. The prerequisites range from thoughtful acknowledgment of the traditional spatial inequities that exist throughout the planning process, considering different social environments of the future green space development, and compiling a diverse set of opinions and perspectives about proposed development. The equity index model in this paper is a flexible tool with the possibility to aid in greater talks around different forms of inclusion, planning, and sustainability. The specific framework employed here was originally developed to support green stormwater infrastructure planning in Philadelphia, PA (Heckert and Rosan 2016; Heckert and Rosan 2018) and was intended as an adaptable model that could be modified for other locations and planning purposes.

Case Study - Frederick County, Maryland

Frederick County, Maryland (Figure 1), and the City of Frederick have decided to formally address climate change. The municipalities have joined hundreds of local governments nationwide by passing a Climate Emergency Resolution (CEMWG 2021). In doing so, the Climate Emergency Mobilization Workgroup (CEMWG) was formed and tasked with compiling recommendations to achieve two main goals: (1) implementing policy and actions through the lens of climate change, and (2) reducing greenhouse gas emissions. The CEMWG recognizes that an effective climate response and resiliency plan must consider historically disadvantaged communities and those currently experiencing hardship and unfairness. Using this basis as a framework, the needs-based equity approach can utilize a Geographic Information Systems (GIS) index model to spatially communicate and identify areas of feasibility and need fulfilling the workgroup's goals. The model presented in this paper aims to address three objectives:

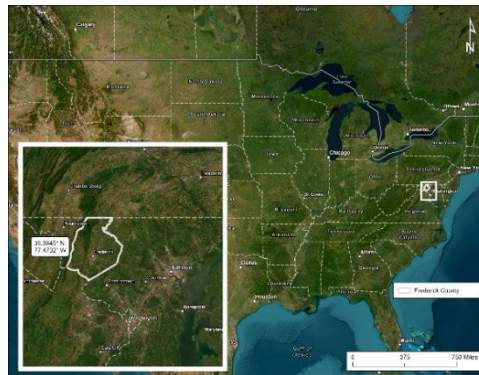


Figure 1. Overview map of Frederick County, MD.

- (1) Prioritization of areas defined as feasible locations for afforestation efforts.
- (2) Prioritization of areas not included in the feasibility model.
- (3) Investigation regarding how changes in weighting equity variables influence areas of need or significance.

DATA AND METHODS

Feasibility Model

Feasibility as mentioned throughout this paper refers to areas that present opportunities for afforestation and meet realistic criteria towards achieving both policy implementation and tangible climate change mitigation results. Areas of feasibility were determined through a geospatial model based on data from Frederick County, the Chesapeake Bay Program, and various State Agencies, including the Maryland Department of Environment (MDE) and Department of Planning. To determine feasibility for afforestation, areas of the county proximate to streams and existing forests were considered to be suitable. Within those suitable areas, low vegetation and shrub areas were included as feasible, while land use types such as high-density residential, mineral mining, historical easements, the development pipeline, soil types needed for agricultural activities, and rights of way were eliminated as infeasible due to the level of development and the needs of agriculture within the county. The output from this analysis is a highly detailed map of sub-parcel level data flagging suitable areas for potential afforestation efforts.

Once the suitability criteria were combined to identify all feasible sites for afforestation, parcel ownership data was overlaid to identify landowners who may be interested in being connected to resources that would help protect riparian areas of property. The resulting parcel feasibility map (Figure 2) highlights the parcels with the highest acreage of feasible land. Most of the parcels containing these suitable areas are on the edges of agricultural lands, while substantial acreage can be found on residential properties. The average parcel size containing land suitable for afforestation efforts is 1.17 acres, indicating potential for smaller scale, community driven initiatives.

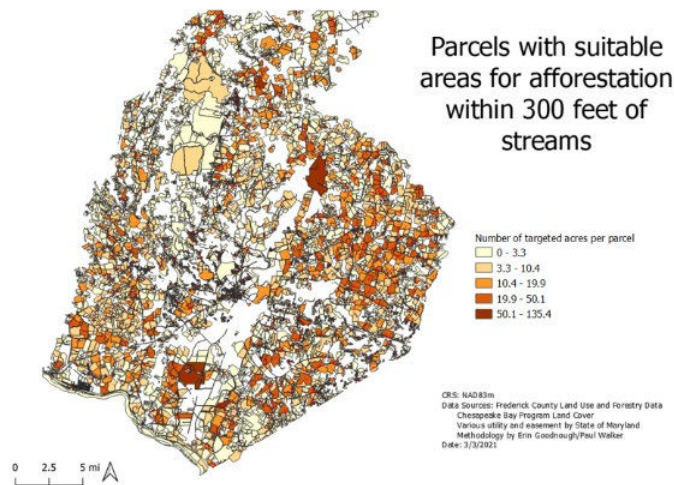


Figure 2. Parcel-level afforestation feasibility.

High-Density Residential Model

The process of calculating feasibility was precise and methodical. However, the decision to exclude the land use type of high-density residential may be omitting significant and influential areas directly related to the idea of a needs-based equity approach to afforestation. As such, an additional model was created to capture this missing component of data. Using the State of Maryland's Land Use Land Cover GIS layer, the high-density residential land cover classification was isolated to identify areas with high need for tree canopy cover despite the infeasibility of afforestation.

Equity Index Model

The equity index model provides a classified visual representation of need delineated by a specific geographical boundary. A series of index variables were set as inputs, allowing a user to assign numerical weights to factors that might indicate need for afforestation or increase tree canopy. The data was sourced from the Environmental Protection Agency's Environmental Justice Mapping Tool (EJScreen) 2020 results, the US Census Bureau's American Community Survey 2019 results, the United Way's Asset Limited, Income Constrained, Employment (ALICE) 2018 data, the United States Department of Agriculture 2017 data, United State Geological Survey 2020 data, the State of Maryland 2014 GIS Catalogue, and Frederick County 2020 GIS Catalogue. To evaluate Frederick County at the most granular level while still being able to find relevant data sources, the collected data was focused on the Census Geography Block Group (BG) scale.

All told, 22 variables were included in the initial equity index model in consultation with members of the CEMWG, as they represent the intended users of the index. These represented factors used by Heckert and Rosan (2016) in a similar equity index in addition to factors deemed locally important by the CEMWG. The variables included: Medicaid Recipients, Supplemental Security Income (SSI) Recipients, Supplemental Nutrition Assistance Program (SNAP) Recipients, Minority Status, Low Income Status, Adults Who Have Not Completed High School, Residents Under the Age of Five, Residents Over the Age of 64, Residents Experiencing Linguistic Isolation, Disability Status, Occupancy Status - Vacant, No Access to Vehicles, Asset Limited Income Constrained Employed (ALICE) Residents, Tree Canopy Cover, Park Access, Impervious Land Cover, Proximity to Traffic, Ozone Levels, Particulate Matter (2.5) Levels, Land Surface Temperature, Food Desert, and Poverty Status.

Land Surface Temperature data was collected using the Earth Explorer tool from USGS. Summer months were queried including 0-10% cloud coverage for Landsat 8 – OLI/TIRS imagery. The imagery analyzed in the model was collected by Landsat on July 29, 2020. Tree Canopy Coverage data was sourced from The Chesapeake Conservancy 2014 raster imagery. Attributes were reclassified and zonal statistics was calculated using GIS to determine average canopy coverage for each BG.

Each variable data source was initially formatted as a percentage of the corresponding BG (e.g., 12% of the BG living in poverty). The percentages were standardized so each BG was assigned a score for each factor ranging from zero to one, where zero indicated the lowest level of need within the county and one represented the highest.

After each variable was standardized for every BG in Frederick County, the data was compiled in a table. The equity model uses the aggregated table to multiply the user's inputted weight by each variable's standardized score and summing the totals across all variables to output a final, weighted value for each of the 190 BGs comprising Frederick County.

Use Cases and Scenarios

The first step in the process of answering the three questions of this paper was to establish a baseline equity map of Frederick County. This was accomplished by assigning all 22 variables an index weight of one. BGs with the highest composite scores represented areas of greatest need. The baseline output model was symbolized, for visual representation, using the quantile method of five classes. BGs in the fifth class corresponded to the top 20% of need, which would be the focus of the model when further analyzing changes in feasibility, high-density residential spaces, and scenarios of differing equity variable weights. Once the baseline model was established, three additional scenario models were run. The additional models were intended to demonstrate how the idea of assessing equity can change based not only on definition, but what inputs are justified and selected to create the definition. Each model included six variables established by the statistical significance and provision of benefits derived from using at least four variables in an analysis of tree allocation from Almeter et al. (2018). The first model only included variables related to the built environment – Land Surface Temperature, Ozone Levels, Park Access, Particulate Matter (2.5) Levels, Proximity to Traffic, Tree Canopy Cover. The second model accounted for solely demographic population indicators of vulnerability – Disability Status, Minority Status, No Access to Vehicles, Poverty Status, Residents Under the Age of Five, Residents Over the Age of 64. The use of Land Surface Temperature, Minority Status, Particulate Matter (2.5) Levels, Poverty Status, and Tree Canopy Cover were included based on a prioritization analysis conducted for the Bronx, New York (Nyelele and Kroll 2021). The final model presented a combination of built environment and demographic variables – Disability Status, Land Surface Temperature, Minority Status, Ozone Levels, Particulate Matter (2.5) Levels, Poverty Status. The included variables were weighted with a score of one, and all other variables

received a score of zero. The BGs in the top 20% for each scenario were identified for continued analysis and comparison.

This process resulted in the output of four sets of 38 BGs each representing the highest need regions of the county. Prioritizing which BGs should be the focus for afforestation initiatives will be determined by the single BG with the highest equity (most inequitable) score for each scenario based on differing environmental and demographic variables. Additionally, it will be noted where the BG is in reference to Frederick City limits for the purpose of informing further discussion around responsibilities and resource sharing for climate change mitigation efforts from the county and city agency perspectives.

RESULTS

The feasibility analysis of suitable areas for afforestation efforts calculated approximately 27,192 acres of opportunity across all of Frederick County. The county also contains 3,112 acres of high-density residential space and 187,503 acres of tree canopy. However, it is not realistic nor an appropriate use of resources to try and evaluate afforestation proposals from such a large scope. The following scenarios will highlight how an equity index model can prioritize policy decision making, compare and prioritize areas not captured in an initial definition of feasibility, and illustrate differences in equity outcomes based on varying inputs.

Baseline Model

Figure 3 demonstrates BGs in the baseline model of greatest need containing 679 feasible acres (5.4%), 2,233 acres of tree canopy cover (17.9%), and 1,059 acres of high-density residential land use (8.5%) across 12,506 total acres. Nearly 53% of the BGs were located within Frederick City Limits. The most inequitable BG, receiving the highest index score, was 240217505032. This BG contained eight feasible acres (13.1%), 13 acres of tree canopy cover (21.3%), and 35 acres of high-density residential land use (57.4%) across 61 total acres. BG 240217505032 is located 100% within the city limits.

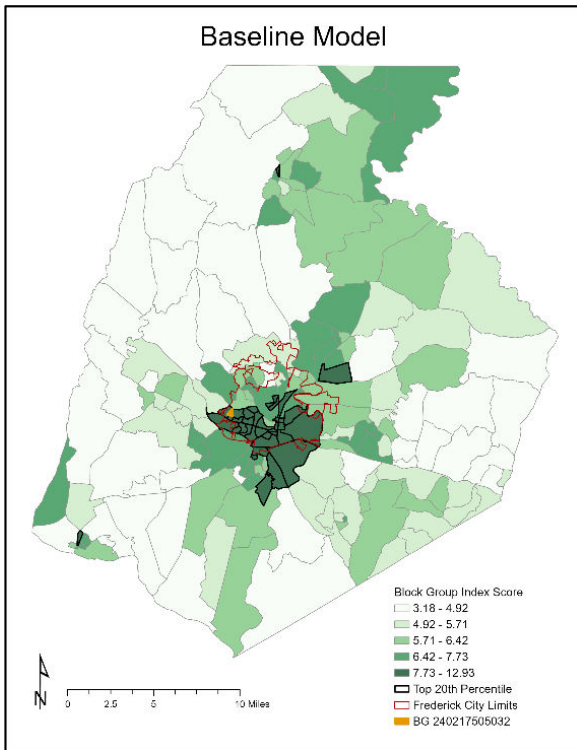


Figure 3. Baseline model.

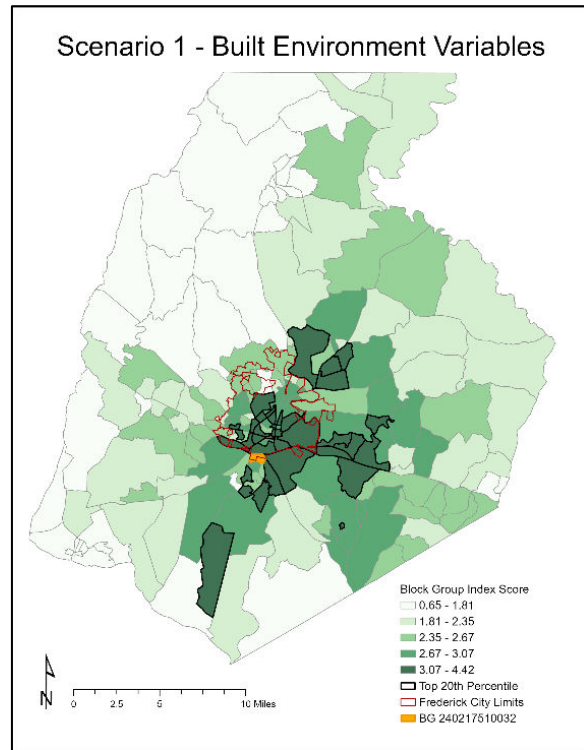


Figure 4. Scenario One- built environment model.

Built Environment (Scenario One)

BGs in the first scenario of greatest need contained 1,251 feasible acres (4.7%), 5,687 acres of tree canopy cover (21.6%), and 1,044 acres of high-density residential land use (4.0%) across 26,378 total acres. Roughly 23% of the BGs were located within Frederick City Limits. The most inequitable BG, receiving the highest index score, was 240217510032, which is highlighted in Figure 4. This BG contained four feasible acres (1.5%), 29 acres of tree canopy cover (11.2%), and 95 acres of high-density residential land use (36.5%) across 260 total acres. BG 240217510032 is located 52% within the city limits.

Demographics (Scenario Two)

BGs in the second scenario of greatest need contained 2,679 feasible acres (6.8%), 10,784 acres of tree canopy cover (27.3%), and 895 acres of high-density residential land use (2.3%) across 39,519 total acres. Approximately 14% of the BGs were located within Frederick City Limits. The most inequitable BG, receiving the highest index score, was 240217510033. This BG contained 119 feasible acres (4.9%), 396 acres of tree canopy cover (16.4%), and two acres of high-density residential land use (0.1%) across 2,419 total acres. BG 240217510033 is located 8% within the city limits, as depicted in Figure 5.

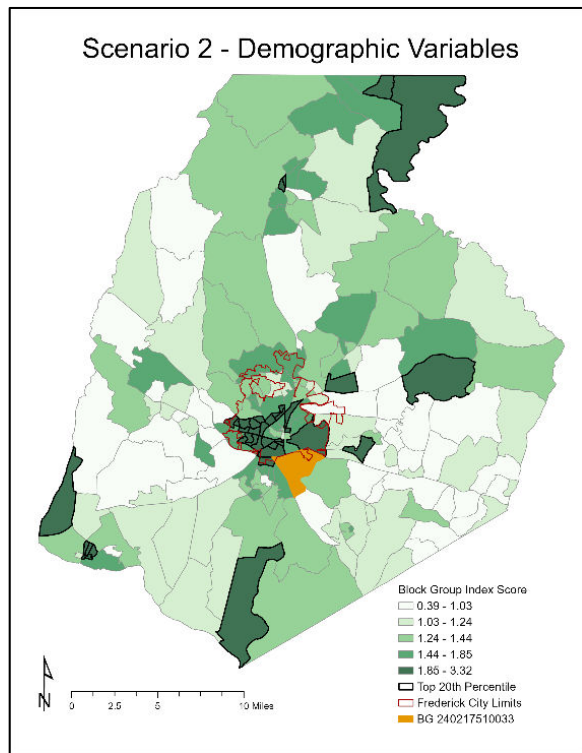


Figure 5. Scenario Two- Demographic model.

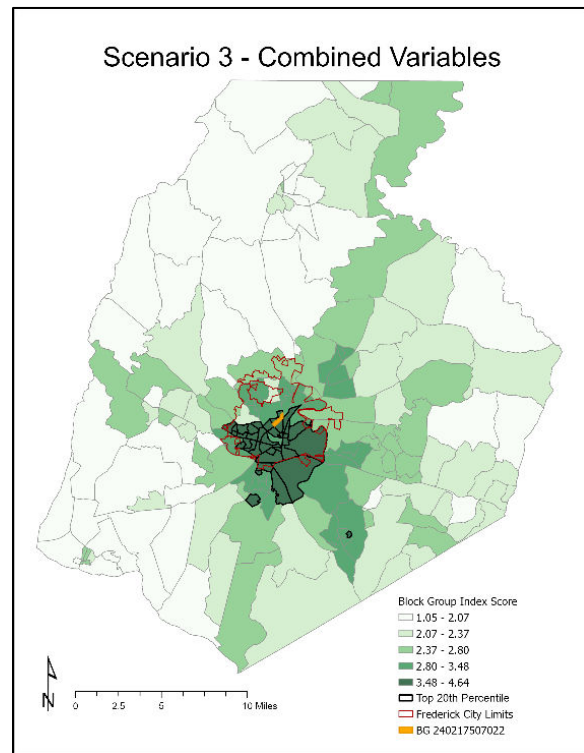


Figure 6. Scenario Three- Combined variables model.

Combined (Scenario Three)

Figure 6 represents the combined scenario, where BGs in the third scenario of greatest need contained 604 feasible acres (5.6%), 1,895 acres of tree canopy cover (17.6%), and 1,138 acres of high-density residential land use (10.6%) across 10,777 total acres. 64% of the BGs were located within Frederick City Limits. The most inequitable BG, receiving the highest index score, was 240217507022. This BG contained nine feasible acres (10.1%), 14 acres of tree canopy cover (15.7%), and 21 acres of high-density residential land use (23.6%) across 89 total acres. BG 240217507022 is located 100% within the city limits.

DISCUSSION

A visual comparison for each of the scenarios reveals how changing equity inputs influenced the spatial location of greatest need. The BGs of greatest inequity for the baseline model were mostly concentrated to the center of the county, straddling Frederick City Limits. This included two small outlier BGs situated approximately ten miles from the majority clustering. The baseline results featured 53% of highest need BGs located within the city limits, yet most of the remaining BGs are still bordering the city, indicating greatest need for the baseline model in urban and suburban classifications with much less rural impact. This stands out in stark contrast to the initial parcel-level afforestation feasibility map (Figure 2), from which most of the high need areas were excluded as infeasible.

The first scenario, focusing on built environment variables, shows a greater deviation from the city limits and nearly double the size of BGs of greatest need from the baseline model, 26,378 acres vs 12,506 acres. Additionally, the most affected BGs are located on the eastern half of the county to the south and southwest. These regions are closest to Washington D.C. and Baltimore, which could influence a poorly built environment, designed for heavy, car-centric commuters. Scenario two, focusing on only demographic indicators, resulted in the greatest deviation of BGs from the center of the county, while representing the largest size of BGs from each scenario, 39,519 acres. Only 14% of scenario two overlapped with Frederick City. Scenario two had significant presence in rural areas of the county. Burkittsville (pop. 151), Emmitsburg (pop. 2,814), Libertytown (pop. 950), and Adamstown (pop. 2,372) are large BGs, located on the outer borders of the county, the farthest distance from Frederick City (pop. 65,239) in any of the model’s scenarios (Frederick County 2010). The third scenario, which was a combination of built environment and demographic variables, produced BGs highly concentrated to the center of the county, 64% of which overlapped in city limits, and had the overall smallest BG area with 10,777 acres.

Table 1. Acreage Comparison Between Model Scenarios.

| Element | Scenario | BG | Element BG Acres | Total BG Acres | % BG Acres |
|--------------------------|------------|--------------|------------------|----------------|------------|
| Feasibility | Baseline | 240217505032 | 8 | 61 | 13.1 |
| | Scenario 1 | 240217510032 | 4 | 260 | 1.5 |
| | Scenario 2 | 240217510033 | 119 | 2419 | 4.9 |
| | Scenario 3 | 240217507022 | 9 | 89 | 10.1 |
| High-Density Residential | Baseline | 240217505032 | 35 | 61 | 57.4 |
| | Scenario 1 | 240217510032 | 95 | 260 | 36.5 |
| | Scenario 2 | 240217510033 | 2 | 2419 | 0.1 |
| | Scenario 3 | 240217507022 | 21 | 89 | 23.6 |
| Combined | Baseline | 240217505032 | 43 | 61 | 70.5 |
| | Scenario 1 | 240217510032 | 99 | 260 | 38.1 |
| | Scenario 2 | 240217510033 | 121 | 2419 | 5.0 |
| | Scenario 3 | 240217507022 | 30 | 89 | 33.7 |

The decision to prioritize a tree afforestation program based solely on the largest amount of feasible land would result in policy makers selecting scenario two to pinpoint BG 240217510033, containing 119 feasible acres, as the region of focus. This BG has 13 times more feasible space than the most inequitable BG in scenario three, and nearly 30 times more space than the most inequitable BG in scenario one. However, BG 240217510033 contains the most tree canopy cover in total and as a percentage of overall BG size, 13 times more than the BG in scenario one with the second most coverage. This hypothetical situation demonstrates how well-meaning decision efforts can select a relatively resourced area, neglecting locations of greater need. None of the scenarios meet the minimum acceptable tree canopy cover threshold of 30%, yet scenario two has 38% more coverage than scenario one.

Incorporating high-density residential areas into the final selection process greatly improves the available space for afforestation and creates a realistic path for scenario one and three to meet the minimum tree canopy cover threshold of 30%. The acreage required for each scenario to achieve the tree canopy threshold was not possible using solely the initial parameters defining feasibility. Again, this situation demonstrates how variable inputs and decision making intended for positive outcomes can overshadow or exclude what might be a better use of resources to achieve policy goals in more meaningful and impactful ways.

Table 2. Tree Canopy Comparison Between Model Scenarios.

| Element | Scenario | BG | Element BG Acres | Total BG Acres | % BG Acres | Acres Needed for 30% Threshold |
|----------------|---------------|--------------|------------------------|----------------------|------------------|---|
| Tree Canopy | Baseline | 240217505032 | 13 | 61 | 21.3 | 5 |
| | Scenario 1 | 240217510032 | 29 | 260 | 11.2 | 49 |
| | Scenario 2 | 240217510033 | 396 | 2419 | 16.4 | 330 |
| | Scenario 3 | 240217507022 | 14 | 89 | 15.7 | 13 |

There are limitations to the equity index model. First, the idea of feasible space for afforestation includes an ample amount of land located on residential properties. Depending on costs to the resident, it may be challenging to obtain participation, especially for those who are already financially constrained. Second, while the feasibility model does an excellent job pinpointing afforestation opportunity at the parcel level, it may not be realistic to use this metric as a means of analysis in higher density regions. A separate analysis may be required to adapt a climate change mitigation strategy for high density land. Trying to apply afforestation techniques to crowded city streets might be less effective than programs aimed at urban forestry and a general increase in tree canopy. Third, this model treats the geographic delineations of each BG as uniform. This is not realistic in the sense every space in each BG experiences variables like Poverty or Land Surface Temperature equally. Instances of the variables may be clustered in one or two regions of the BG or perhaps the boundary between BGs accounts for most of the demographic or built environment variables being evaluated. Nevertheless, this methodology still allows for a closer examination of defined, spatially significant areas. Finally, there will never be a perfect formula to calculate exact instances of need. This model attempts to include an array of variables that have been identified as relevant to the study of environmental justice, afforestation, and urban inequities.

CONCLUSIONS

The equity index model presented in this paper demonstrates how areas of greatest need can be prioritized based on a calculated concept of feasibility. The paper then investigates how decisions to exclude or include certain variables in those calculations may overlook or alter the intended policy outcomes, all while spatially representing the changes in location for regions of need based on variable inputs. BGs receiving the highest index scores are not geographically constrained throughout Frederick County. Each scenario yields outcomes of varying levels of interaction that range between the densely populated urban landscape of Frederick City, to the sparsely inhabited rural historic village of Burkittsville. Need exists throughout Frederick County, which makes the equity index model a valuable tool for policy makers and community members. Ultimately, the goal is to create an index that is easily accessible to every stakeholder involved in the study area. This would provide great opportunity for increasing participatory planning and community involvement, truly working to fulfill an equitable approach to climate change mitigation efforts.

REFERENCES

- Almeter, A., A. Tashie, A. Procter, T. McAlexander, D. Browning, C. Rudder, L. Jackson, and R. Araujo. 2018. A needs-driven, multi-objective approach to allocate urban ecosystem services from 10,000 Trees. *Sustainability (Switzerland)* 10 (12).
- Beyer, K. M. M., A. Kaltenbach, A. Szabo, S. Bogar, F. Javier Nieto, and K. M. Malecki. 2014. Exposure to neighborhood green space and mental health: Evidence from the survey of the health of wisconsin. *International Journal of Environmental Research and Public Health* 11 (3):3453–3472. Climate Emergency Mobilization Work Group (CEMWG), 2021, *Climate Response and Resilience*,

https://www.mobilizefrederick.org/_files/ugd/793224_86d724fb9047489896e823edf2e1a3f6.pdf. Accessed Mar. 2021.

Dimke, K. C., T. D. Sydnor, and D. S. Gardner. 2013. The effect of landscape trees on residential property values of six communities in Cincinnati, Ohio. *Arboriculture and Urban Forestry* 39 (2):49–55.

Doney, S. C., D. S. Busch, S. R. Cooley, and K. J. Kroeker. 2020. The impacts of ocean acidification on marine ecosystems and reliant human communities. *Annual Review of Environment and Resources* 45:83–112.

Dvorak, A. C., H. M. Solo-Gabriele, A. Galletti, B. Benzecry, H. Malone, V. Boguszewski, and J. Bird. 2018. Possible impacts of sea level rise on disease transmission and potential adaptation strategies, a review. *Journal of Environmental Management* 217:951–968. <https://doi.org/10.1016/j.jenvman.2018.03.102>.

Frederick County Maryland. The Division of Planning and Permitting. 2010. *2010 U.S. Census Population*. <https://www.frederickcountymd.gov/8015/US-Census-Populations> (last accessed 24 February 2022).

Haase, D., S. Kabisch, A. Haase, E. Andersson, E. Banzhaf, F. Baró, M. Brenck, L. K. Fischer, N. Frantzeskaki, N. Kabisch, K. Krellenberg, P. Kremer, J. Kronenberg, N. Larondelle, J. Mathey, S. Pauleit, I. Ring, D. Rink, N. Schwarz, and M. Wolff. 2017. Greening cities – To be socially inclusive? About the alleged paradox of society and ecology in cities. *Habitat International* 64:41–48.

Hacker, J., and C. Roberts. 2013. The science of climate change. *Two Degrees: The Built Environment and Our Changing Climate* (1):3–17.

Heckert, M., and C. D. Rosan. 2016. Developing a green infrastructure equity index to promote equity planning. *Urban Forestry and Urban Greening* 19:263–270. <http://dx.doi.org/10.1016/j.ufug.2015.12.011>.

Heckert, M., and C. D. Rosan. 2018. Creating GIS-based planning tools to promote equity through green infrastructure. *Frontiers in Built Environment* 4 (May):1–5.

Horney, J. A., I. M. Karaye, A. Abuabara, S. Gearhart, S. Grabich, and M. Perez-Patron. 2021. The Impact of Natural Disasters on Suicide in the United States, 2003-2015. *Crisis* 42 (5):328–334.

Hou, G., C. O. Delang, X. Lu, and R. Olschewski. 2019. Valuing carbon sequestration to finance afforestation projects in China. *Forests* 10 (9):1–20.

Knight, T., S. Price, D. Bowler, A. Hookway, S. King, K. Konno, and R. L. Richter. 2021. How effective is ‘greening’ of urban areas in reducing human exposure to ground-level ozone concentrations, UV exposure and the ‘urban heat island effect’? An updated systematic review. *Environmental Evidence* 10 (1):1–39.

Kuehler, E., J. Hathaway, and A. Tirpak. 2017. Quantifying the benefits of urban forest systems as a component of the green infrastructure stormwater treatment network. *Ecohydrology* 10 (3):1–11.

Łaszkiewicz, E., and D. Sikorska. 2020. Children’s green walk to school: An evaluation of welfare-related disparities in the visibility of greenery among children. *Environmental Science and Policy* 110 (Sept 2019):1–13.

Lin, B., J. Meyers, and G. Barnett. 2015. Understanding the potential loss and inequities of green space distribution with urban densification. *Urban Forestry and Urban Greening* 14 (4):952–958. <http://dx.doi.org/10.1016/j.ufug.2015.09.003>.

Lin, J., and Q. Wang. 2021. Are street tree inequalities growing or diminishing over time? The inequity remediation potential of the MillionTreesNYC initiative. *Journal of Environmental Management* 285 (July 2020):112207. <https://doi.org/10.1016/j.jenvman.2021.112207>.

Lynas, M., B. Z. Houlton, and S. Perry. 2021. Greater than 99% consensus on human caused climate change in the peer-reviewed scientific literature. *Environmental Research Letters* 16 (11).

- Mackay, K. D., C. L. Gross, and M. Rossetto. 2018. Small populations of fig trees offer a keystone food resource and conservation benefits for declining insectivorous birds. *Global Ecology and Conservation* 14:e00403. <https://doi.org/10.1016/j.gecco.2018.e00403>.
- Mader, S. 2019. Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area. *Mitigation and Adaptation Strategies for Global Change* :519–536.
- Nijnik, M., G. Pajot, A. J. Moffat, and B. Slee. 2013. An economic analysis of the establishment of forest plantations in the United Kingdom to mitigate climatic change. *Forest Policy and Economics* 26:34–42. <http://dx.doi.org/10.1016/j.forpol.2012.10.002>.
- Nowak, D. J., S. Hirabayashi, A. Bodine, and E. Greenfield. 2014. Tree and forest effects on air quality and human health in the United States. *Environmental Pollution* 193:119–129.
- Nyelele, C., and C. N. Kroll. 2021. A multi-objective decision support framework to prioritize tree planting locations in urban areas. *Landscape and Urban Planning* 214 (June):104172. <https://doi.org/10.1016/j.landurbplan.2021.104172>.
- Plantinga, A. J., T. Mauldin, and D. J. Miller. 2017. An Econometric Analysis of the Costs of Sequ ester ing Car bon in Forests. *Climate Change* 81 (November):347–359.
- Rigolon, A. 2016. A complex landscape of inequity in access to urban parks: A literature review. *Landscape and Urban Planning* 153:160–169. <http://dx.doi.org/10.1016/j.landurbplan.2016.05.017>.
- Rigolon, A., and T. L. Flohr. 2014. Access to parks for youth as an environmental justice issue: Access inequalities and possible solutions. *Buildings* 4 (2):69–94.
- Rossati, A. 2017. Global warming and its health impact. *International Journal of Occupational and Environmental Medicine* 8 (1):7–20.
- Seddon, N., A. Smith, P. Smith, I. Key, A. Chausson, C. Girardin, J. House, S. Srivastava, and B. Turner. 2021. Getting the message right on nature-based solutions to climate change. *Global Change Biology* 27 (8):1518–1546.
- Straka, T. M., M. von der Lippe, C. C. Voigt, M. Gandy, I. Kowarik, and S. Buchholz. 2021. Light pollution impairs urban nocturnal pollinators but less so in areas with high tree cover. *Science of the Total Environment* 778:146244. <https://doi.org/10.1016/j.scitotenv.2021.146244>.
- Ulmer, J. M., K. L. Wolf, D. R. Backman, R. L. Tretheway, C. J. Blain, J. P. O’Neil-Dunne, and L. D. Frank. 2016. Multiple health benefits of urban tree canopy: The mounting evidence for a green prescription. *Health and Place* 42:54–62.
- Watkins, S. L., and E. Gerrish. 2018. The relationship between urban forests and race: A meta-analysis. *Journal of Environmental Management* 209:152–168. <https://doi.org/10.1016/j.jenvman.2017.12.021>.
- Watkins, S. L., S. K. Mincey, J. Vogt, and S. P. Sweeney. 2017. Is Planting Equitable? An Examination of the Spatial Distribution of Nonprofit Urban Tree-Planting Programs by Canopy Cover, Income, Race, and Ethnicity. *Environment and Behavior* 49 (4):452–482.
- Zandieh, R., J. Martinez, and J. Flacke. 2019. Older adults’ outdoor walking and inequalities in neighbourhood green spaces characteristics. *International Journal of Environmental Research and Public Health* 16 (22).